Who Pays for Your Rewards?
Redistribution in the Credit Card Market

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Introduction

Motivation

- **Individuals make costly mistakes when using financial products**

  In the case of credit cards:

  1. **Overindebtedness** (Gross & Souleles 2002; Heidhues & Kőszegi 2010)
  2. **Suboptimal repayment** (Ponce et al. 2017; Gathergood et al. 2019)

- **Banks can design financial products to exploit these mistakes**
  - Salient, front-loaded benefits combined with shrouded, back-loaded costs (DellaVigna & Malmendier 2004; Heidhues & Kőszegi 2017)

$\Rightarrow$ **Redistribution from naïve to sophisticated consumers**

- Naïve consumers might underestimate the costs while sophisticated ones might rake in the benefits (Gabaix & Laibson 2006)

Research Questions

- Despite the *theoretical* predictions, examining redistribution from naïve to sophisticated consumers *empirically* is challenging:
  - Financial decision-making of individuals depends on hard-to-measure variables
  - It requires granular data on costs and benefits of financial product usage
- This paper $\rightarrow$ credit card reward programs as an ideal laboratory
  1. **Consumer perspective:** Is there a redistribution across consumers in the credit card market induced by reward programs? Who benefits and who pays for it? What type of suboptimal behavior explains the effects?
  2. **Bank perspective:** Do banks design this financial product to incentivize adoption and usage? How much do they profit?
  3. **Spatial Disparities:** Do reward credit cards exacerbate income disparities?

Literature Contribution

Primer on Credit Card Reward Programs

- Reward programs offer benefits to cardholders per dollar spent on the credit card (cash back, miles, points)
- Credit cards and reward programs as a feature of credit cards prevalent in the US (and in other Anglo-Saxon countries e.g., UK, Canada, Australia)
  - As of 2019: 75% of US consumers use credit cards and reward cards account for 60% of new card originations
  - The largest US banks paid out **$35bn in rewards** (entertainment market = $36bn)
- From a consumer perspective:

$$\underbrace{\text{Net Rewards}_{i,t}}_{\text{Cardholder Profit/Loss}} = \underbrace{\text{Rewards}_{i,t}}_{\text{Potential Benefit}} - \underbrace{\text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}}_{\text{Potential Costs}}$$

$\Rightarrow$ *These costs and benefits are likely not equally distributed across cardholders*

Data

Data

- Source: Federal Reserve Board's Y-14M data (banks $>$\$100bn assets)
  - Covers 70% of outstanding balances on consumer credit cards (CFPB 2019)
- Monthly account-level data on:
  - Accumulated rewards, interest and fee payments, spending and unpaid balances, credit limits, FICO scores, consumer income, zip code & more
- **Cross-section of 238 million consumer cards as of March 2019**

Descriptive Statistics

Consumer Perspective

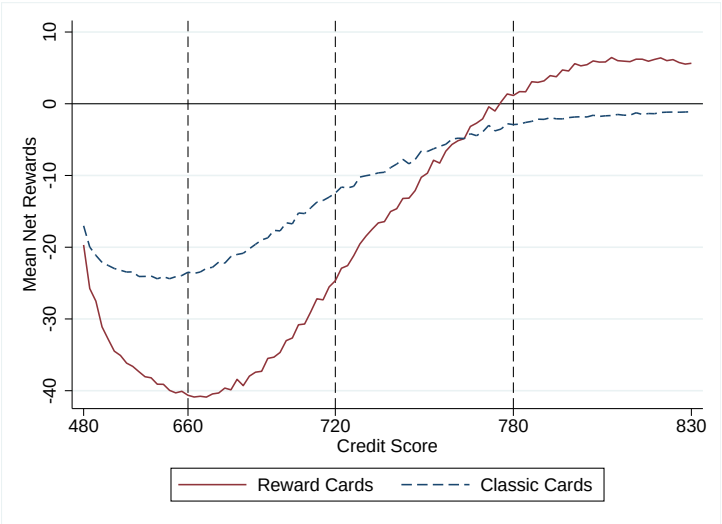
Methodology

- Specification:

$$\text{Net Reward}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

  - *Reward Card* = 1 if card offers rewards; and 0 otherwise
  - D^F = FICO bucket dummy variable ($<$ 660 = Sub-prime; 660-720 = Near-prime; 720-780 = Prime; $>$ 780 = Super-prime), as of March 2018
  - $\alpha_{f,w,z,b}$ = $\text{FICO}_{Q100} \times \text{Income}_{Q100} \times$ zip Code $\times$ Bank FE
  - X_i^m = Card-level controls (credit limit, amount past due, card age, joint account indicator, fraud dummy)
  - X_j^n = Consumer-level controls (deposit relationship indicator, lending relationship dummy, total number of cards the consumer has with the bank, a workout program dummy, bankruptcy indicator)

Net Rewards Across the FICO Distribution

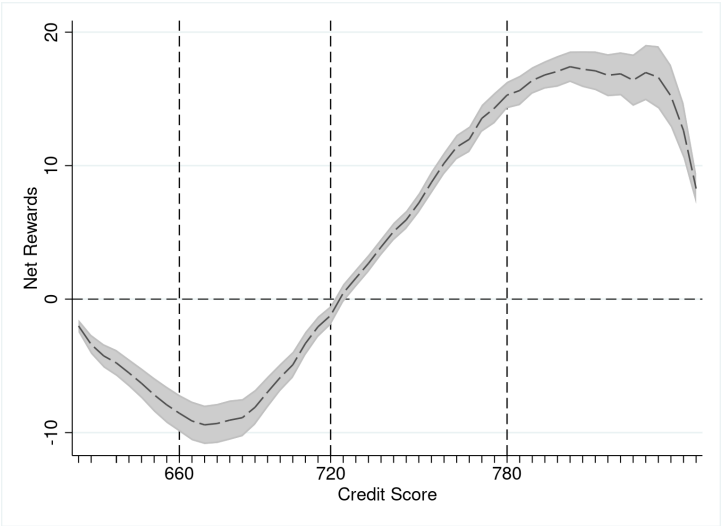


Regression Analysis: Net Rewards

$$\text{Net Rewards}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	(1)	(2)	(3)	(4)
Reward Card	4.66***	3.88***	3.48***	
	(0.30)	(0.37)	(0.38)	
Reward Card × Sub-Prime				-5.37***
				(0.67)
Reward Card × Near-Prime				-6.80***
				(0.69)
Reward Card × Prime				7.28***
				(0.44)
Reward Card × Super-Prime				16.05***
				(0.93)
Card Controls& Cardholder Controls	Y	Y	Y	Y
FE: Bank × Zip × Income	Y	N	-	-
FE: Bank × Zip × FICO	N	Y	-	-
FE: Bank × Zip × Income × FICO	N	N	Y	Y
Observations		237,573,278		

Regression Analysis: Net Rewards Across the FICO Distribution



Robustness: Net Rewards

	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	0.617***		1.94***		1.77***	
	(0.15)		(0.51)		(0.37)	
Reward Card × Sub-Prime		-0.49***		-1.02***		-5.53***
		(0.09)		(0.16)		(1.07)
Reward Card × Near-Prime		-0.95***		-1.79***		-8.53***
		(0.35)		(0.53)		(0.96)
Reward Card × Prime		1.20***		2.89***		4.08***
		(0.30)		(0.44)		(0.47)
Reward Card × Super-Prime		2.62***		6.50***		14.09***
		(0.34)		(1.20)		(1.03)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	-	-
FE: Bank × Cardholder	-	-	-	-	Y	Y
FE: Bank × Zip × Income × FICO	-	-	Y	Y	-	-
FE: Bank × Zip × Income × FICO × Limit × APR	Y	Y	-	-	-	-
Observations	12,381,801				65,513,743	

Aggregate Net Rewards

- Cardholders with negative net rewards pay $4.1bn for the use of reward cards and cardholders with positive net rewards earn $1.3bn
- **Annualized redistribution of $15.1bn**
  - Of the $4.1bn paid by cardholders with negative net rewards, 1bn come from sub-prime, 1.6bn from near-prime, 1.1bn from prime, and only 0.4bn from super-prime cardholders
  - Of the $1.3bn earned by cardholders with positive net rewards, only $0.04bn go to sub-prime, $0.13bn to near-prime, $0.41bn to prime, and $0.68bn to super-prime cardholders

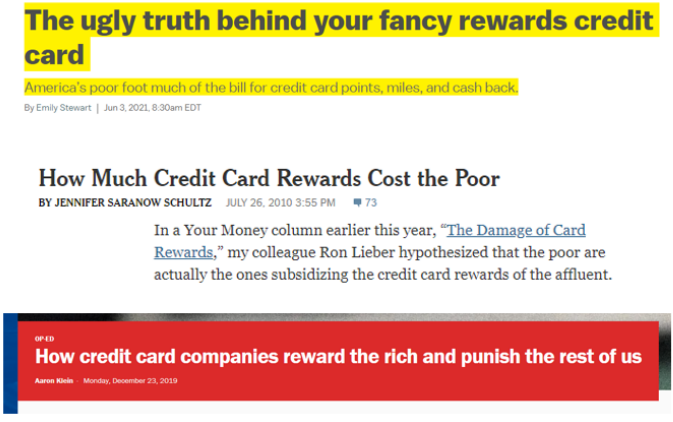
Regression Analysis: Net Reward Components

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Rewards		Interest Charges		Total Fee Charges	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	6.38***		2.20***		0.70***	
	(0.35)		(0.18)		(0.08)	
Reward Card × Sub-Prime		1.79***		6.38***		0.78***
		(0.14)		(0.69)		(0.10)
Reward Card × Near-Prime		4.83***		10.86***		0.78***
		(0.27)		(0.75)		(0.12)
Reward Card × Prime		8.39***		0.34		0.77***
		(0.31)		(0.24)		(0.08)
Reward Card × Super-Prime		9.45***		-7.09***		0.50***
		(0.38)		(0.64)		(0.06)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations				237,573,278		

Interpretation

A Reverse Robin Hood Effect?



The ugly truth behind your fancy rewards credit card

America's poor foot much of the bill for credit card points, miles, and cash back.

By Emily Stewart | Jun 3, 2021, 8:30am EDT

How Much Credit Card Rewards Cost the Poor

BY JENNIFER SARANOW SCHULTZ JULY 26, 2010 3:55 PM 73

In a Your Money column earlier this year, "The Damage of Card Rewards," my colleague Ron Lieber hypothesized that the poor are actually the ones subsidizing the credit card rewards of the affluent.

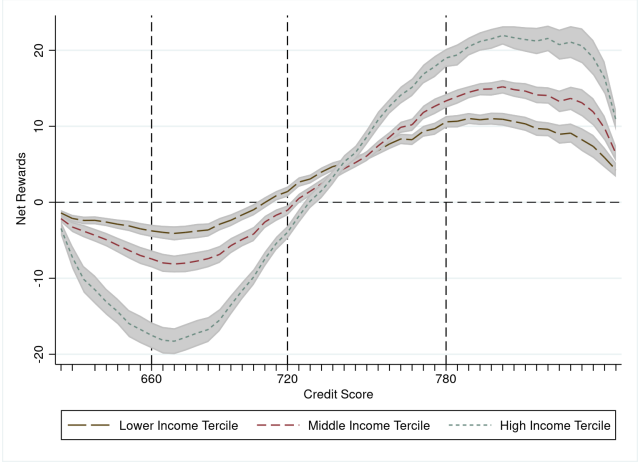
OP-ED

How credit card companies reward the rich and punish the rest of us

Aaron Klein · Monday, December 23, 2019

Net Rewards of Reward Cards by Income Group

Credit scores and income are not strongly correlated (Beer, Ionescu, and Li, 2018) FICO Distribution



Net Rewards by Income Group

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Lower Tercile of Income Distribution		Middle Tercile of Income Distribution		Upper Tercile of Income Distribution	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.86***		2.73***		5.36***	
	(0.20)		(0.28)		(0.61)	
Reward Card × Sub-Prime		-2.56***		-4.88***		-12.75***
		(0.34)		(0.59)		(1.18)
Reward Card × Near-Prime		-2.36***		-5.80***		-13.15***
		(0.45)		(0.58)		(0.77)
Reward Card × Prime		5.93***		6.29***		8.70***
		(0.33)		(0.37)		(0.58)
Reward Card × Super-Prime		9.71***		13.60***		20.10***
		(0.60)		(0.71)		(1.03)
Card Controls	Y	Y	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y	Y	Y
Observations	75,159,536		79,540,729		82,873,013	

Top Income Distribution

Credit Card Rewards and Financial Sophistication

FICO scores capture behaviors associated with lack of financial sophistication

$\Rightarrow$ FICO score as a measure of financial sophistication (Agarwal et al. 2015)

Empirical tests:

1. **Over-indebtedness:** Do reward cards induce $\uparrow$ spending by consumers, causing some of them to have $\uparrow$ unpaid balances, incurring $\uparrow$ interest and fees?
   - Identification strategy: compare, in a DiD setting, similar consumers with *bank-initiated credit line increases* in a reward vs. classic card in the same month
2. **Suboptimal repayment:** Are misallocated payments $\uparrow$ for reward than classic credit cards among low-FICO consumers?
   - Identification strategy: compare misallocated payments of reward vs. classic cards within the same consumer among those with *multiple credit cards*

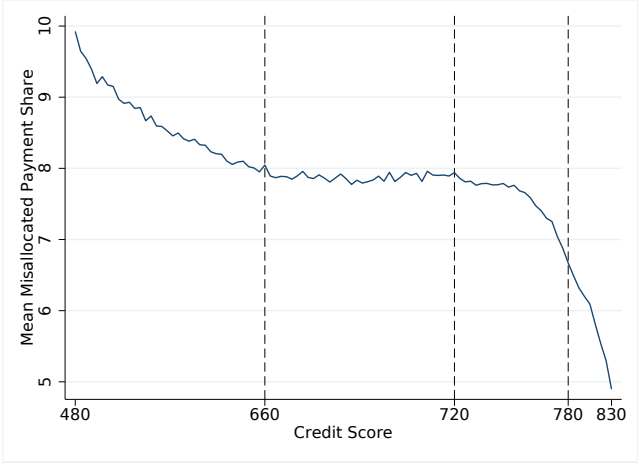
Over-indebtedness: DiD Analysis

$$\Delta Y_{i(\pm 6m)} = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Δ Spending		Δ Payments		Δ Unpaid Balances	
	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	75.77***		31.96***		19.17**	
	(6.83)		(3.72)		(8.79)	
Reward Card × Sub-Prime		59.75***		5.06		33.82***
		(6.43)		(3.12)		(11.24)
Reward Card × Near-Prime		62.88***		4.53		25.25*
		(7.18)		(4.29)		(13.53)
Reward Card × Prime		89.03***		73.19***		4.83
		(7.98)		(6.17)		(12.16)
Reward Card × Super-Prime		164.85***		153.22***		-28.20
		(14.14)		(13.22)		(25.26)
Mean Y (All Cardholders)	1067.50		1098.16		2865.21	
Card Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Cardholder Controls (Pre-Period)	Y	Y	Y	Y	Y	Y
Income and FICO (Pre-Period)	Y	Y	Y	Y	Y	Y
Spending and Payments (Pre-Period)	Y	Y	Y	Y	Y	Y
FE: Bank × Zip	Y	Y	Y	Y	Y	Y
Observations	1,236,604					

Sub-Optimal Repayment Behavior

Misallocated payments: Share of payments that were incorrectly made on a cheaper card that should have been made on more expensive card(s).



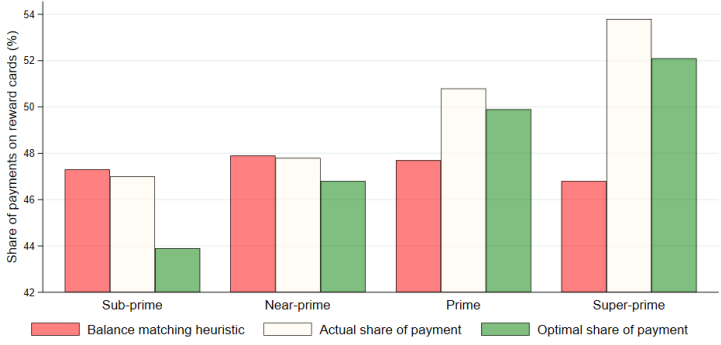
Regression Analysis: Share of Misallocated Payments

$$\text{MP Share}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_j + \sum_m X_i^m + \varepsilon_i$$

	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.24***		1.71***		1.74***	
	(0.28)		(0.33)		(0.37)	
Reward Card × Sub-Prime		2.65***		3.74***		4.18***
		(0.20)		(0.25)		(0.30)
Reward Card × Near-Prime		0.76***		1.15***		1.08***
		(0.28)		(0.34)		(0.35)
Reward Card × Prime		0.14		0.35		0.13
		(0.37)		(0.41)		(0.42)
Reward Card × Super-Prime		0.07		0.30		0.12
		(0.41)		(0.44)		(0.47)
Restrictions on consumers:						
At least 2 cards with revolving debt	Y	Y	Y	Y	Y	Y
Did not pay full balance on all cards	Y	Y	Y	Y	Y	Y
Made minimum payment on all revolving cards & paid > than the minimum on at least 1	N	N	Y	Y	Y	Y
Have different APRs on all revolving cards	N	N	N	N	Y	Y
Card Controls	Y	Y	Y	Y	Y	Y
FE: Cardholder × Bank	Y	Y	Y	Y	Y	Y
Observations	21,288,917		16,136,165		12,858,916	

Misallocated Payments and Heuristics

- Sub-prime and near-prime cardholders follow a **balance-matching heuristic** (i.e., paying cards according to their outstanding balance), as in Gathergood et al. (2019)
- Prime and super-prime cardholders' repayment behavior is more correlated with the optimal allocation rule



Bank Perspective

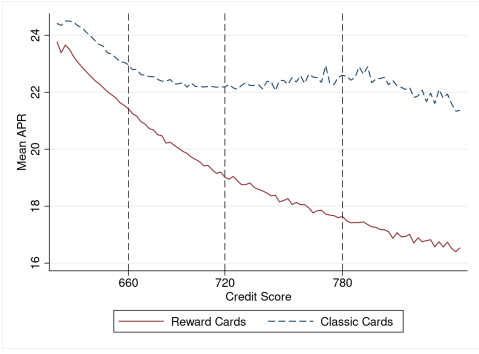
Rewards from the Bank Perspective

- **Bank perspective**
  - Do banks lure people into reward cards?
  - How do banks profit across the FICO distribution?
- Definition of bank profits:

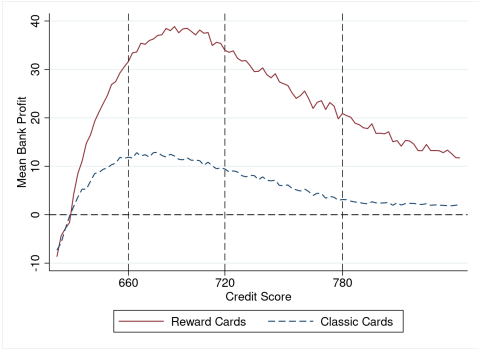
$$\text{Bank Profit/Loss}_i = \text{Interest Paid}_i + \text{Total Fees}_i + \text{Interchange Income}_i - \text{Rewards}_i - \text{Realized Charge-Offs}_i$$

  - Interchange Income = (1.5% - 2.5%) $\times$ Purchase Volume
  - Realized Charge-Offs = Charge-off if account is 180 days delinquent

Pricing and Profits



(a) APRs



(b) Bank Profits

$\Rightarrow$ Banks use aggressive pricing to lure consumers into reward cards

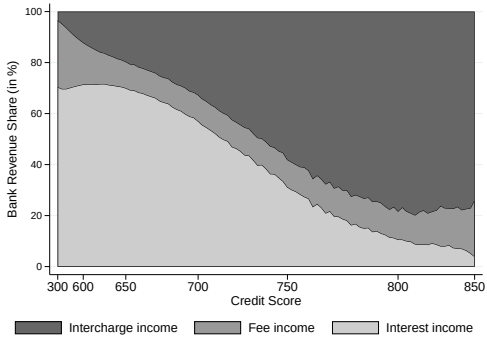
$\Rightarrow$ Banks profits are highest in the middle of the FICO distribution

Regression Analysis: APRs and Bank Profits

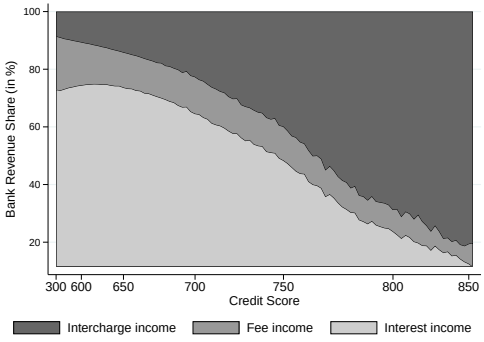
$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	APR		Profit	
	(1)	(2)	(3)	(4)
Reward Card	-0.96***		7.37***	
	(0.19)		(0.69)	
Reward Card × Sub-Prime		-0.20**		4.06***
		(0.09)		(1.45)
Reward Card × Near-Prime		-0.469***		15.28***
		(0.16)		(1.16)
Reward Card × Prime		-1.34***		8.95***
		(0.26)		(0.48)
Reward Card × Super-Prime		-1.65***		1.32***
		(0.27)		(0.48)
Card Controls	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y
Observations		237,573,278		

Bank Revenue Shares Across the FICO Distribution



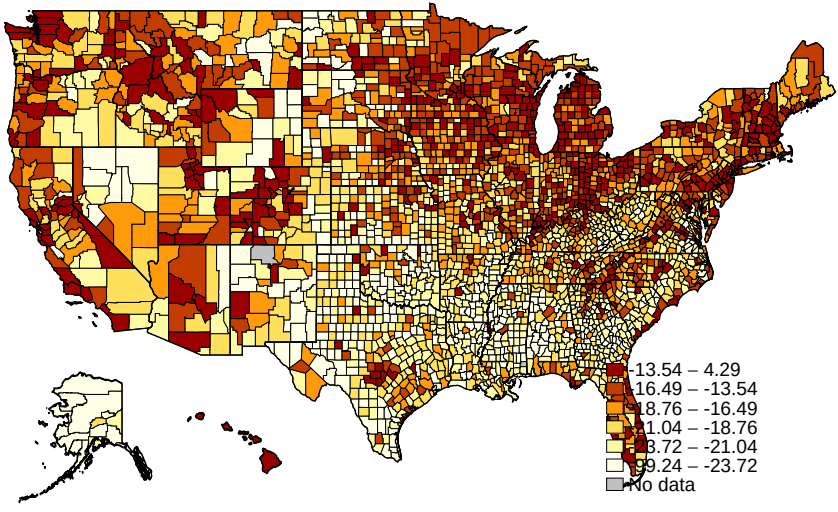
(c) Reward cards



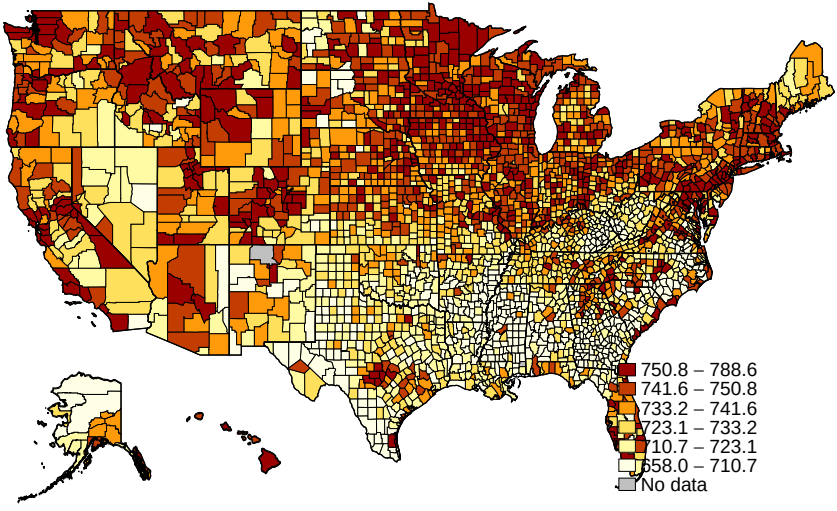
(d) Classic cards

Spatial Disparities

Geography of Net Rewards



Geography of FICO Scores



Geography of Net Rewards

$$\text{Net Reward}_{i,z} = \sum_k \beta^k X_z^k + \gamma \times \overline{CreditScore}_z + \varepsilon_{i,z}$$

	(1)	(2)	(3)	(4)	(5)	(6)
Education	0.29***	-0.01				
	(0.02)	(0.02)				
Income			0.21***	0.00		
			(0.02)	(0.02)		
Black Population Share					-0.14***	0.00
					(0.01)	(0.01)
Credit Score		0.19***		0.18***		0.19***
		(0.01)		(0.00)		(0.00)
Observations	237,573,278					

Conclusion

Conclusions

1. **Consumer perspective:** sophisticated individuals profit from reward cards, at the expense of naïve ones

   Results not driven by income, but by financial sophistication

   - *Over-indebtedness:* reward cards induce ↑ spending, causing naïve consumers to have higher unpaid balances
   - *Suboptimal repayment:* naïve consumers have higher misallocated payments on reward cards and follow a (costly) balance-matching heuristic

2. **Bank perspective:** through low APRs banks lure consumers into reward cards

   - Despite different revenue sources, banks profit across the entire FICO distribution

3. **Spatial Disparities:** reward cards transfer income from less to more educated, poorer to richer, and high- to low-majority areas

Appendix

Literature Contribution

- Cross-subsidy from naïve to sophisticated consumers in retail financial markets
  - Theoretical: DellaVigna and Malmendier (2004); Gabaix and Laibson (2006); Heidhues and Kőszegi (2010, 2017)
  - Empirical: Guiso, Pozzi, Tsoy, Gambacorta, and Mistrulli (2021); Fisher, Gavazza, Liu, Ramadorai, and Tripathy (2021)
    - Empirical evidence on cross-subsidization in mortgage markets.
  - Our paper: Evidence on redistribution in credit card markets.
- Credit card rewards
  - Hayashi (2009); Schuh, Shy, and Stavins (2010); Felt, Hayashi, Stavins, and Welte (2020); Levitin (2008); Sarin (2019)
    - Focus on redistribution from cash users to credit card users.
  - Our paper: Focus on redistribution within credit card users.

Back

Computing Monthly Net Rewards (1/2)

- Definition of net rewards

$$\text{Net Rewards}_{i,t} = \text{Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}$$

- Note: Variable *Gross Rewards* not contained in the dataset
- But: We do observe *Cumulative Rewards* each month

$$\text{Cumulative Rewards}_{i,t} = \text{Cumulative Rewards}_{i,t-1} + \text{Rewards}_{i,t} - \text{Redemptions}_{i,t}$$

$\Rightarrow$ Goal: Estimate *Rewards* from data

Computing Monthly Net Rewards (2/2)

1. Calculate effective reward rate of card *i*

$$\text{Card-Specific Reward Rate}_{i,t} = \frac{\Delta\text{Cumulative Rewards}_{i,t}}{\text{Purchase Volume}_{i,t}}$$

   - Note: This reward rate is correct if *Redemptions* are zero

2. Cluster credit cards at the individual product level *k* by:
   - Bank $\times$ Credit card type $\times$ Product type $\times$ Card network $\times$ Reward type $\times$ Fee type $\times$ Fee level

$$\text{Estimated Reward Rate}_{i,t} = Q_{50}^{k}\left(\text{Card-Specific Reward Rate}_{i \in k,t}\right)$$

3. Calculate *Rewards*

$$\text{Rewards}_{i,t} = \text{Estimated Reward Rate}_{i,t} \times \text{Purchase Volume}_{i,t}$$

Descriptive Statistics

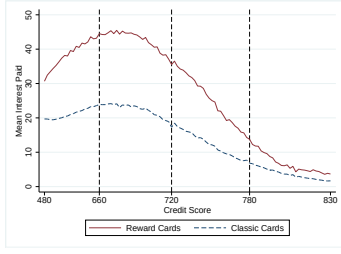
Back

	All Cards			Reward Cards	Classic Cards
	Mean	Median	SD	Mean	Mean
Panel A. Net Reward Variables					
Rewards (in $)	4.69	0.00	20.42	9.30	0.00
Interest Charges (in $)	14.38	0.00	37.91	18.34	10.36
Fee Charges (in $)	2.64	0.00	11.01	3.33	1.93
Net Rewards (in $)	-12.33	0.00	44.41	-12.37	-12.29
Panel B. Other Variables					
APR (in %)	20.63	21.49	7.15	18.64	22.64
Bank Profits (in $)	14.53	1.11	232.94	22.54	6.39
FICO Score	729.60	742.00	75.65	743.22	715.77
Borrower Income (in $k)	88.44	60.00	1863.36	98.02	78.71
Credit Limit (in $k)	7.37	5.00	7.90	10.42	4.28
Amount Past Due (in $)	10.26	0.00	172.45	8.19	12.37
Age of Card (in years)	7.43	4.83	7.36	7.61	7.24
Joint Account (0/1)	0.02	0.00	0.15	0.03	0.02
Fraud Flag (0/1)	0.00	0.00	0.06	0.00	0.00
Deposit Relationship With Same Bank (0/1)	0.19	0.00	0.39	0.28	0.10
Lending Relationship With Same Bank (0/1)	0.08	0.00	0.27	0.11	0.05
No. Cards With Same Bank (0/1)	2.11	2.00	1.25	1.89	2.34
Workout Program (0/1)	0.01	0.00	0.07	0.00	0.01
Bankruptcy Flag (0/1)	0.00	0.00	0.05	0.00	0.00
Observations		237,573,278		119,730,353	117,842,925

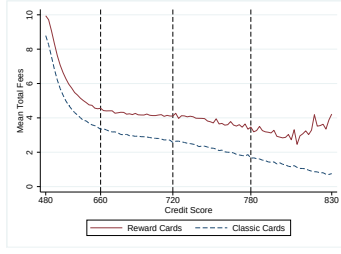
Net Reward Components Across the FICO Distribution

$$\text{Net Rewards}_{i,t} = \text{Rewards}_{i,t} - \text{Interest Paid}_{i,t} - \text{Total Fees}_{i,t}$$

(e) Rewards



(f) Interest Paid

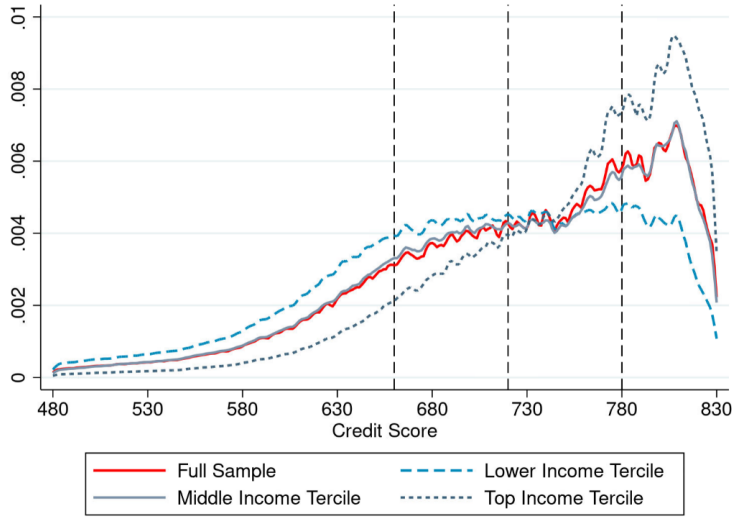


(g) Total Fees

$\Rightarrow$ High-FICO cardholders earn more rewards but pay less interest and fee charges

FICO Distribution by Income

Back



Net Rewards by Top Income Distribution

Back

$$Y_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_{f,w,z,b} + \sum_m X_i^m + \sum_n X_j^n + \varepsilon_i$$

	Top 10% of Income Distribution		Top 5% of Income Distribution	
	(1)	(2)	(3)	(4)
Reward Card	6.96***		7.70***	
	(0.86)		(0.96)	
Reward Card × Sub-Prime		-21.97***		-25.61***
		(1.50)		(1.72)
Reward Card × Near-Prime		-18.35***		-19.43***
		(1.00)		(1.15)
Reward Card × Prime		10.65***		11.77***
		(0.76)		(0.86)
Reward Card × Super-Prime		22.33***		22.24***
		(1.14)		(1.16)
Card Controls	Y	Y	Y	Y
Cardholder Controls	Y	Y	Y	Y
FE: Bank × Zip × Income × FICO	Y	Y	Y	Y
Observations	26,600,689	26,600,689	14,754,880	14,754,880

Computing Misallocated Payments

- Sample of consumers with multiple cards at the same bank
- Rational decision rule:
  1. Make the minimum payment due on all cards
  2. Pay of the card with the highest APR in full
  3. Start paying off cheaper cards after
- We rank all cards of consumer *i* at bank *b* by their APR
- Calculation of misallocated payment (MP) share

$$\text{MP Share} = \begin{cases} \frac{\text{Actual Payment Amount}_{i,b} - \text{Optimal Payment Amount}_{i,b}}{\text{Total Payment Amount}_{i,b}} & \text{if} \quad \text{APA}_{i,b} > \text{OPA}_{i,b} \\ 0 & \text{if} \quad \text{APA}_{i,b} \leq \text{OPA}_{i,b} \end{cases}$$

- Interpretation: Share of payments that were incorrectly made on a cheaper card that should have been made on more expensive card(s).

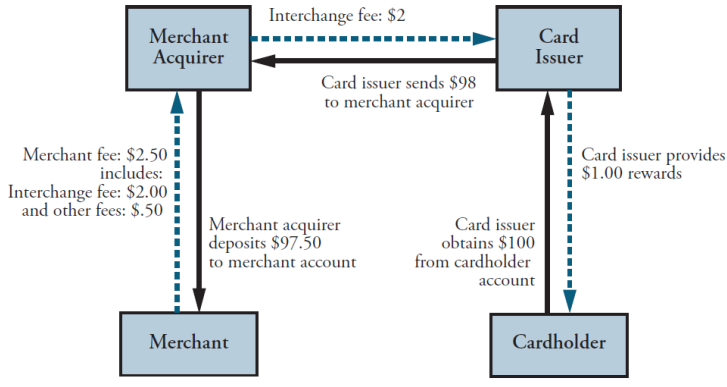
Regression Analysis: Share of Misallocated Payments—Two Cards

$$\text{MP Share}_i = \sum_F \left(\delta^F \times \text{Reward Card}_i \times D^F \right) + \alpha_j + \sum_m X_i^m + \varepsilon_i$$

	(1)	(2)	(3)	(4)	(5)	(6)
Reward Card	1.152***		1.640***		1.741***	
	(0.344)		(0.406)		(0.461)	
Reward Card × Sub-Prime		2.964***		4.113***		4.599***
		(0.278)		(0.313)		(0.375)
Reward Card × Near-Prime		0.398		0.787**		0.825**
		(0.288)		(0.344)		(0.389)
Reward Card × Prime		-0.342		-0.118		-0.224
		(0.380)		(0.427)		(0.471)
Reward Card × Super-Prime		-0.179		0.103		0.004
		(0.498)		(0.547)		(0.590)
Restrictions on consumers:						
At least two cards with revolving debt	Y	Y	Y	Y	Y	Y
Did not pay full balance on all revolving cards	Y	Y	Y	Y	Y	Y
Made minimum payment on all revolving cards & paid > than the minimum on at least 1	N	N	Y	Y	Y	Y
Have different APRs on all revolving cards	N	N	N	N	Y	Y
Card Controls	Y	Y	Y	Y	Y	Y
FE: Cardholders × Bank	Y	Y	Y	Y	Y	Y
Observations	13,080,528	13,080,528	9,909,754	9,909,754	8,862,432	8,862,432

Market Structure of Credit Card Payments

Back

Figure1

PAYMENT AND FEE FLOWS IN FOUR-PARTY SCHEME CARD NETWORKS